A Work Project, presented as part of the requirements for the Award of a

Master's degree in Finance from the Nova School of Business and Economics.

"The Informational Content of Open Interest on Commodity Future Returns"

Niels Linus Mayer N° 58191

Work project carried out under the supervision of:

Professor André Castro Silva

21/05/2025

Abstract: This analysis is building on the initial work by Hong and Yogo (2012) and examines the informational content of commodity futures open interest changes across categories of market participants in the intra- and post-financialization era (2006 – 2024). Using the disaggregated Commitments of Traders report by the Commodity Futures Trading Commission, the study analyzes monthly excess returns of an equally weighted commodity futures portfolio. The analysis finds that a one-standard-deviation increase in open interest by money managers is associated with a 1.10% decline in the expected returns. In contrast, increasing open interest (participation) by producers lead to generally increasing excess returns.

Keywords: Commodity Futures, Financialization of Commodities, Intermediary Asset Pricing, Financial Intermediation

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

Contents

List of Tables

List of Figures

List of Equations

1. Introduction

The last two decades have witnessed a fundamental transformation in global commodity futures markets – the phenomenon of financialization. Beginning in the early 2000s, the commodity futures markets experienced a large inflow of capital, particularly from index investors and institutional funds in order to further diversify their portfolio (Basak and Pavlova 2016). This flood of capital not only shifted the composition of market participants, but according to some academic research also influenced pricing dynamics and risk premia.

While traditional economic theories within commodity futures markets are based on the supply and demand of physical commodities, recent research is challenging their explanatory power. Hong and Yogo (2012) demonstrated that aggregated market participation (i.e. open interest) in the commodity futures market can offer informational content beyond traditional financial and macroeconomic indicators. Building on the initial work by Hong and Yogo (2012), this study is extending the scope into the intra- and post-financialization era (2006 – 2024) and is utilizing the disaggregated Commitments of Traders (DCOT) report published by the Commodity Futures Trading Commission (CFTC).

By analyzing monthly excess returns of an equally weighted commodity portfolio, this study confirms that the predictive power of traditional indicators has diminished. Instead, the positioning of selected market participants revealed to be significant predictors. A one-standard-deviation increase in money managers open interest (mostly speculative motives) is associated with a 1.10% decline in expected excess returns, whereas increasing (imbalanced, short-position driven) producer participation is associated with increasing excess returns. The study challenges the prevailing societal assumption, that participation of speculators generally leads to inflated prices (Irwin et al. 2009). It also aims to enhance the structural understanding of excess returns and to examine the informational content of category-specific position changes in a structurally transformed commodity futures market intra- and post-financialization.

2. Literature Review

This analysis builds on and extends the work of Hong and Yogo (2012) and is situated at the intersection of three major stands of the commodity futures literature.

The first area of research addresses the financialization of the commodity futures markets. Next, the literature review draws on the current stand of predictability of commodity futures (excess) returns. And last, focuses on the growing literature on intermediary asset pricing.

2.1. Financialization of the Commodity Futures Markets

The significant inflow of investment capital from institutional investors into the commodity futures markets in the 2000s is generally described as the financialization of the commodity markets. Traditionally commodity futures markets have been dominated by commercial hedgers using futures to manage price risks. These markets increasingly attracted institutional investors seeking exposure to the asset class of commodities in order to capitalize on diversification benefits and inflation hedging possibilities (Basak and Pavlova 2016; Cheng and Xiong 2014).

There is no consensus among academics as to whether this phenomenon of financialization has impacted the pricing dynamics and market functioning of commodity futures markets. Existing analyses differ widely in terms of time and/or commodities examined. On the one hand, several studies suggest a significant impact of the financialization. Tang and Xiong (2012) analyzed 28 US-traded commodities focusing on the time horizon of 2006 – 2011 and found that there has been an increasing cross-correlation within commodity prices. This implies that price discovery is no longer only reliant on supply and demand for individual commodities but influenced by the "aggregated risk appetite for financial assets and the investment behavior of diversified index investors" (Tang and Xiong 2012, 72). Büyüksahin and Robe (2014) came to similar conclusions when examining daily and weekly returns of commodity and equity indices between 1991 and 2010. They discovered that the correlation between equity and commodity indices has significantly increased due to the participation of hedge funds, thereby reducing the diversification advantages of commodity futures. In addition, Gilbert's (2010) study on corn, soybean and wheat futures covering 2007 to 2008, revealed that index future investments as part of the financialization contributed directly to price increases. These investments were found to function as a funnel for monetary and financial activity and thus directly influence futures prices and actual underlying food prices (Gilbert 2010).

In contrast, other studies reported limited or no measurable impact from financialization on commodity future prices. Hamilton and Wu (2015) were analyzing 12 different agricultural commodities between 2006 – 2012 and found no evidence for a significant impact of index fund activity on futures price movements. Likewise, Büyüksahin and Harris (2011), analyzing the crude oil futures market from 2000 to 2008, concluded that there is no (sufficient) evidence that changes in the positioning of hedge funds or other non-commercial (i.e. speculative) market participants cause price changes.

2.2. Predictability of Commodity Returns

The predictability of commodity futures returns has been a central focus in academic research and is a core focus of this analysis. Existing literature identified three major categories of predictors: macroeconomic, commodity-specific, and broad financial market predictors.

First, commodity prices are intrinsically linked to macroeconomic activity due to the unique characteristics of the asset class. Given the physical nature of commodities, commodity futures rely on global production, consumption, and storage constraints and are therefore sensitive to business cycles, inflation and monetary policy. According to the literature, commodity prices can reflect as well as help forecast macroeconomic fluctuations. Barsky and Kilian (2002) and Alquist et al. (2013) have shown in their work that commodity prices can help explain macroeconomic fluctuations. Meanwhile Gargano and Timmermann (2014) found that inflation, money supply and other macroeconomic indicators can help predict (spot) price movements. Further, Yin and Han (2016) revealed the importance of international macroeconomic driver, showing that Chinese macroeconomic indicators (i.e. production and consumption levels) significantly influence US commodity futures. In addition, Cotter (2023) discovered increased return predictability during times of economic recessions, thus suggesting that macroeconomic conditions are particularly relevant during economic downturns.

Second, academia identified commodity-specific predictors, stemming from the distinctiveness of the commodity asset class and its market. Key predictors, as highlighted by Szymanowska et al. (2014) and Yin et al. (2020) include basis, momentum, liquidity and open interest. Classic asset pricing theories in the commodity-spectrum as the theory of backwardation, proposed by Kaldor (1939) and Keynes (1930), argue that the predictive power of the basis and inventory levels, is based on hedging pressure and storage costs faced by intermediaries exposed to the physical commodities (i.e. producers). These theories focus specifically on the role of producers as they argue that the predictability of commodity futures returns stems from variations in the risk premium that financial traders can earn due to varying excess hedging demands by producers (Hong and Yogo 2012; Cheng and Xiong 2014). Gorton et al. (2007) provide empirical support for the relation between time-varying commodity futures risk premiums and the level of physical inventories, known as the theory of storage. Open interest, sitting at the core of Hong and Yogo (2012) and this analysis, is a recurring predictor. Thus, Floros and Salvador (2016) as well as Ripple and Moosa (2009) reaffirmed that open interest possesses explanatory power for futures volatility (for energy commodities), even when controlling for the related market volume.

The third cluster of key predictors are broad financial indicators. These include returns from other asset classes such as stocks or fixed income, price-dividend ratios, the term spread (i.e. the difference between long and short term (US) government bonds) and the yield spread.

The significance of these predictors can be motivated by two theories. First, due to the financialization of commodity futures markets (as shown in Chapter 2.1.) the correlation between returns of commodity futures markets and other asset classes has increased. Secondly, these predictors influence the associated discount rates or risk premiums of commodity returns for investors and thus need to be accounted for (Cotter 2023).

Overall, the existing literature indicates that commodity return predictability is multi-faceted with evidence supporting all three categories. Recent literature is providing a complementary perspective focusing on the importance of different market participants as part of the intermediary asset pricing theory (see Chapter 2.3.).

2.3. Intermediary Asset Pricing in Commodity Futures Markets

Traditional asset pricing models within the commodity futures markets including the theory of backwardation and the hedging pressure (see Chapter 2.2.) focus on the role of commercial producers, who hedge their price risks and offer a risk premium in return. More recently, the emerging intermediary asset pricing theory shifts the focus towards sophisticated (financial) intermediaries to understand risk sharing dynamics.

In combination with the financialization of the commodity markets and the increased influence of financial investors, this framework is building upon the critical role of intermediaries as marginal investors (He et al. 2017). (Financial) intermediaries act as market makers connecting producers, consumers and investors by bearing risk and providing liquidity (Yin et al. 2020). Moreover, following Liu et al. (2018) the (financial) intermediaries ensure higher liquidity in the markets, support price stability and increase certainty of trade execution for other participants. Resulting from this central role within commodity futures markets, different studies confirmed the influence of the intermediary financial health on asset returns. According to Yin et al. (2020) a negative shock to the intermediary equity capital decreases asset prices by reducing their risk-bearing capacity, known as the equity constraint framework. Supporting this, Haddad and Muir (2021) confirmed the relevance of intermediaries as they found that a significant share of the risk premia of commodity futures is related to the intermediary health. Additionally, their work revealed that asset classes with a higher degree of intermediation exhibit higher return predictability (Haddad and Muir 2021).

Cheng et al. (2015) contribute to the relevance of intermediation with the introduction of the theory of convective risk flows in commodity futures. Their work focuses on the risk-sharing dynamics between financial intermediaries and commercial market participants and highlights the importance of the direction of trade initiation. Their study reveals that, particularly in times of high volatility, risk is passed from financial intermediaries to commercial participants, in return for higher excess returns (Cheng et al. 2015). Extending this dynamic, Kang et al. (2020) identified a second return premium in commodity futures markets (in addition to the existing hedging theory premium), related to the provision of short-term liquidity. Their work emphasizes the role of commercial market participants as intermediaries, which act as liquidity providers for speculative market participants. In return for the provision of liquidity, intermediaries receive higher excess returns (Kang et al. 2020).

The literature generally concludes that understanding "who trades helps predict the joint distribution of commodity [...] returns" (Büyüksahin and Robe 2014, 38-39). In this context, Bonnier (2021) found that traditional speculators are responsible for the increased volatility in some commodity markets. On the other hand, Brunetti et al. (2016) concluded that speculators did not destabilize commodity futures markets, when studying commodity markets from 2005 to 2009. Hedge fund participation was found to be negatively correlated with volatility and positively correlated with returns in markets such as corn, crude oil and natural gas. In contrast, swap dealers (see Chapter 3.1.) did not exert significant influence on volatility or returns.

However, it has been shown that increased underlying commercial activity is associated with increased volatility and return variation (Brunetti et al. 2016).

In summary, emerging intermediary asset pricing theory complements traditional asset pricing models. While the literature largely agrees on the relevance of intermediation, there are different opinions regarding the underlying mechanism and time-varying trade initiation and intermediation. The disagreement underscores the relevance of this study by focusing on category-specific positioning flows within the intra- and post financialization era.

3. Data and Portfolio Construction

The following chapter outlines the utilized data, the construction of the monthly commodity futures portfolio and summary statistics covering the intra- and post financialization period.

3.1. Commodity Futures and Spot Price Data

Commodity futures contracts were originally developed to allow producers and consumers to hedge against price fluctuations of physical underlying commodities. The futures contract entails the obligation to buy or sell a certain amount of a commodity for a specified price at a specified time in the future. To enhance the liquidity and tradability, US futures exchanges regulated by the Commodity Futures Trading Commission (CFTC) have standardized contract terms with regard to contract size, delivery process, day and location of delivery and acceptable quality of the commodity (CFTC 2025c). The continuous commodity futures daily price data is provided by LSEG (formerly Refinitiv Eikon) and covers a period from June 2006 to December 2024 – due to the availability of open interest data by the CFTC (see Chapter 3.2.).

In line with Hong and Yogo (2012) this analysis excludes futures contracts with less than one month to maturity or more than 13 months, as these months are typically less liquid or may exhibit distorted pricing dynamics. While other comparable papers such as Cotter (2023) build their analysis around (replicating) investible commodity indices, this analysis, following Hong and Yogo (2012) and Gorton et al. (2007), refers to a weighted portfolio of commodities divided into four sectors – energy, agriculture, livestock and metals (see Table A.I.). While Hong and Yogo (2012) incorporated 30 different commodities, this analysis only includes 28 commodities due to data availability.

Spot prices of commodities for the same period are also extracted from LSEG. Due to data limitations, spot prices are not sufficiently available for every commodity. But as spot prices are only utilized in an aggregated form for the construction of the basis predictor (see Chapter 3.4.1.), this is neglected. Detailed information regarding the included commodities, their spot and futures price availability, as well as the sector mapping can be found in Table A.I..

3.2. Open Interest Data

Open interest, as defined by the CFTC, refers to the total number of outstanding futures contracts that have not yet been offset by transaction, delivery or exercise (CFTC 2025a). It is reported as the number of outstanding contracts, not the associated US-dollar value and thus represents a measure of market activity and liquidity. Increases in open interest indicate capital inflow into the futures markets and vice versa. By construction, the total number of long futures contracts always equals the aggregated number of short futures contracts and thus equal open interest (CFTC 2025b).

To ensure market transparency and to prevent market manipulation, the CFTC requires clearing members, futures commission merchants and foreign brokers to report all futures positions above a prespecified threshold to the CFTC (CFTC 2025d). According to the CFTC (2025b), the report covers approx. 70 – 90% of the total open interest in any given market at any time.

Since 2009 the CFTC publishes the “Disaggregated Commitment of Traders” report (DCOT), retroactively covering data from June 2006. Initially covering 22 major commodity markets, the DCOT now covers over 270 specified commodities. The report is published on Friday with the data of market closure on the previous Tuesday of the same week. The DCOT classifies market participants into four categories:

Category 1 – Producer/merchant/processor/user: Market participants with a clear hedging motive, predominantly utilizing the futures markets to manage or hedge risks associated with producing, processing or handling physical commodities (CFTC 2025b).

Category 2 – Swap dealer: Entities that "deal primarily in swaps for a commodity and uses the futures markets to manage or hedge the risk associate with those swaps transactions" (CFTC 2025b, 3). The swap dealer's counterparties are likely commercial (Category 1) or speculative traders (Category 3) (CFTC 2025b). In the literature, the swap dealer category is often interpreted as a noisy proxy for the positions of Commodity Index Traders (CIT). CITs account for a large share of the capital inflow during the financialization (Cheng et al. 2015).

Category 3 – Money manager: This category includes commodity trading advisors, commodity pool operators or unregistered funds, that "[…] are engaged in managing and conducting organized futures trading on behalf of their clients" (CFTC 2025b, 3). As clients are typically hedge funds or investment funds, these positions are generally viewed as more speculative (Kang et al. 2020).

Category 4 – Other reportables: This represents the residual category for all market participants that are subject to reporting requirements but do not fall into Category 1 – 3.

Market participants are categorized based on the assessment by the CFTC regarding their predominant business activity by commodity. Additionally, the classification of a market participant may differ between commodities. As market participants are classified on commodity/entity-level and not on a transaction-level, categories are not clearly distinguished between hedging and speculative motives (CFTC 2025b).

3.3. Macroeconomic Data

The macroeconomic data used in this report is based exclusively on the Federal Reserve Economic Data (FRED) provided by the St. Louis FED from June 2006 to December 2024. The selected macroeconomic predictors are described in more detail in Chapter 3.4.1..

3.4. Portfolio Construction and Main Predictor

This study focuses on monthly excess returns of an equally weighted commodity futures portfolio as the dependent variable. While Hong and Yogo (2012) do not specify the exact intervals of the constructed monthly observations, this study follows common academic practice by calculating Tuesday-to-Tuesday observations (Bonnier 2021). This aligns with the weekly reporting of Tuesday end-of-day data by the CFTC on Friday (CFTC 2025b). Monthly growth rates are calculated by using the last Tuesday of the previous month and the last Tuesday of the current month, creating 223 observations between June 2006 and December 2024.

Following Hong and Yogo (2012) the analysis is based on an equally weighted portfolio across commodity sectors. Commodities are categorized into four commodity sectors (see Table A.I.). Within each sector, each commodity-specific growth rate is weighted equally. While Hong and Yogo (2012) argue that this approach is mitigating concentration risk, an equally weighted portfolio does not represent actual sector distribution and thus leads to an overrepresentation of smaller sectors (esp. livestock, see Figure A.I.).

Following academic convention, portfolio returns are calculated as the excess returns of the commodity futures over the average one-month T-bills for the same period. This adjustment reflects the assumption that the commodity futures are fully collateralized and therefore the interest of the monthly T-bills has to be deducted as interest earned on collateral (Cotter 2023).

Open interest growth rates are based on the aggregated notional US-dollar value differences. The notional value of open interest for each commodity is computed by multiplying the average closing price (in US-Dollar) of the futures by the underlying quantity of a futures contract and the reported open interest (Hong and Yogo 2012). This analysis utilizes growth rates instead of levels of open interest to circumvent the underlying stochastic growth trend that Hong and Yogo (2011) have identified the trend in earlier studies. Although it is rather uncommon in the existing literature, Hong and Yogo (2012) decide to employ 12-month geometric averages to the open interest growth rates. The authors are arguing that this smooths the time series and reduces short-term noise (Hong and Yogo 2012).

3.4.1. Other Predictor Variables

As the literature review identified various influential predictors, the analysis is deliberately restricted to the predictors used in the benchmark study by Hong and Yogo (2012). The inclusion of these predictors allows to control for their informational content and isolate the contribution of the categorized open interest data. The predictor variables include:

Broad financial predictors:

- *Short-rate*: Defined as the Tuesday-Tuesday monthly average yield on the one-month T-bills. FRED data with daily reporting-schedule, ensuring exact interval overlap.
- *Yield-spread*: Defined as the Tuesday-Tuesday monthly average spread between Moody's AAA corporate bond yield and the one-month T-bill. FRED data with daily reporting-schedule, ensuring exact interval overlap.

Macroeconomic predictors:

- *Chicago Fed National Activity Index (CFNAI)*: Measure of real US-economic activity which is available on a monthly basis by FRED. Monthly data provides no exact interval overlap with Tuesday-Tuesday monthly growth rates.

Commodity-specific predictors:

- *Historic portfolio excess returns:* Computed as the 12-month geometric averages of the portfolio's past excess returns. It is intended to control for long-term momentum in the time series (Hong and Yogo 2012).
- *Aggregated commodity basis*: The basis equals the relative difference between futures and spot prices while accounting for the respective time difference. As spot prices represent actual daily transaction prices in the spot market, there is reduced standardization and data availability (see Table A.I.). Following Hong and Yogo (2012) we impute missing spot prices by taking the respective price of the future closest to expiry as a proxy for the spot price. To account for potential large outliers in the spot prices, we form an equally weighted average of the median basis within each sector. Calculated as:

$$Basis_{i,t,T} = \left(\frac{F_{i,t,T}}{S_{i,t}}\right)^{1/(T-t)} - 1 \qquad \text{(I.)}$$

with F ≙ futures price, S ≙ spot price, i ≙ commodity and T – t ≙ time to maturity

- *Market imbalance*: Represents the net positioning of producers (Category 1) and is weighted equally across sectors. The imbalance is calculated as:

$$Imbalance = \frac{(Short\_\$Value\_Sector_{\ Category1} - Long\_\$Value\_Sector_{Category1})}{(Short\_\$Value\_Sector_{Category1} + \ Long\_\$Value\_Sector_{Category1})} \qquad \text{(II.)}$$

Following the predictive nature of this analysis, all predictor variables have to be lagged. As macroeconomic variables are published with delays, researchers like Cotter (2023) decided to lag macroeconomic variables by two months to ensure data availability. As the purpose of this analysis is not to provide a commercial-viable forecasting setting but to investigate the informational content of predictors, all predictors are lagged only one month.

3.5. Summary Statistics

Table I. reports the summary statistics for the monthly excess returns of the commodity futures portfolio and the predictors for the period of June 2006 till December 2024 containing 223 observations. Additionally in squared-brackets, Table I. contains the values of the benchmark study by Hong and Yogo (2012) covering the period 1965 to 2008.

Table I: Summary Statistics of the Portfolio

				Correlation with					
Variable	Mean (%) [1965-2008[1]]	Standard deviation (%) [1965-2008[1]]	Autocorrelation [1965-2008[1]]	12-m. Returns [1965-2008[1]]	12-m. Open Interest [1965-2008[1]]	Basis [1965-2008[1]]	Market Imbalance [1965-2008[1]]	Short rate [1965-2008[1]]	Yield spread [1965-2008[1]]
Monthly Returns Growth Rate	0.60 [0.64]	3.77 [4.62]	0.22 [0.07]						
12-month geometric average	*0.56 [1.08]*	*1.42 [1.30]*	*0.94 [0.93]*						
Monthly Open Interest Growth Rate (All)	0.93	6.36	0.15						
12-month geometric average	*0.75 [1.47]*	*2.00 [2.06]*	*0.92 [0.90]*	*0.89 [0.51]*					
Cat1: Monthly Open Interest Growth Rate	1.06	7.15	0.08						
12-month geometric average	*0.85*	*2.15*	*0.92*	0.86	0.97	0.17	0.57	0.17	-0.16
Cat2: Monthly Open Interest Growth Rate	0.86	6.17	0.31						
12-month geometric average	*0.75*	*2.27*	*0.94*	0.88	0.96	0.14	0.53	0.13	-0,07
Cat3: Monthly Open Interest Growth Rate	1.28	8.05	0.07						
12-month geometric average	*0.93*	*2.16*	*0.88*	0.82	0.96	0.13	0.46	0.18	-0.09
Cat4: Monthly Open Interest Growth Rate	1.22	6.59	0.08						
12-month geometric average	*1.04*	*1.98*	*0.93*	0.82	0.96	0.14	0.53	0.13	-0,07
Basis	5.68 [0.14]	6.87 [0.62]	0.77 [0.79]	0.06 [0.03]	0.14 [-0.07]				
Market Imbalance	42.87 [17.84]	7.33 [13.80]	0.90 [0.90]	0.47 [0.44]	0.53 [0.31]	0.42 [0.15]			
Short rate	1.39 [5.52]	1.84 [2.71]	0.99 [0.97]	0.15 [0.05]	0.15 [0.01]	-0.04 [0.24]	-0.34 [0.27]		
Yield spread	2.87 [2.64]	1.64 [1.60]	0.99 [0.92]	-0.11 [-0.35]	-0.08 [-0.10]	0.20 [-0.24]	0.41 [-0.31]	-0.86 [-0.54]	
Chicago Fed National Activity Index	-0.17 [0.01]	1.48 [0.86]	0.16 [0.93]	0.20 [0.29]	0.20 [0.36]	-0.08 [-0.11]	0.07 [0.17]	0.01 [-0.02]	-0.07 [-0.12]

Notes: 1) The table includes benchmark numbers from the paper by Hong & Yogo (2012) covering the time period 1965:12 - 2008:12

Summary statistics for commodity future returns and predictors. The mean, standard deviation, autocorrelation and correlation (not lagged) is reported. The sample period is 2006:06 - 2024:12.

The average monthly excess return of the equally weighted portfolio is 0.60% with a standard deviation of 3.77%. The average excess return is slightly lower than during the benchmark period of Hong and Yogo (2012), which also exhibits a higher standard deviation.

The overall 12-month geometric average of the monthly open interest growth rate is 0.75%, substantially lower than the 1.47% average growth rate reported by Hong and Yogo (2012). This suggests that the period until 2008 incorporates the bulk of the increased capital inflow in the course of the financialization (see Chapter 2.1.), with a slowdown of capital inflow thereafter. While the average growth rate of the open interest aggregate is significantly lower, the standard deviation remains almost unchanged indicating that the time series remains cyclical.

Investigating the origination of the remaining growth in open interest, Category 3 and Category 4 showcase the strongest average growth rates. This suggests that while the evolvement of traditional producers and swap dealer remained rather unchanged, the amount of capital invested under speculative motives grew above average. Category 3 also possesses the highest standard deviation, which may reflect their speculative nature. Notably, Category 1 also displays a comparatively high standard deviation, which may reflect the seasonality of some commodities and the respective seasonal hedging demand, or even their role as intermediaries.

Previous observations from Hong and Yogo (2012) can be confirmed for the updated timeframe of this analysis. We can see that post-financialization, the historically strong positive correlation between 12-month geometric average commodity futures excess returns and open interest is now even stronger. Reinforcing the relevance of open interest as a meaningful predictor. Additionally, both variables remain positively correlated to the CFNAI indicating that stronger economic activity is associated with positive excess returns and open interest growth. In line with the consensus in practice and academia, the yield spread remains negatively correlated with the CFNAI, which demonstrates that in times of economic downturn the yield spread picks up and thus functions countercyclically (Hong and Yogo 2012; Norland 2025).

Nevertheless, there are also differences to the original study. The market imbalance appears much more substantial, and the open interest growth rate is now even stronger correlated with the imbalance of Category 1. Interestingly, this occurs alongside a decline in the standard deviation of the market imbalance, suggesting more persistent positioning. While this initially seems counterintuitive, given commercial market participants tend to be more active in the market for non-hedging related motives (see Chapter 2.3.), the classification of commercial participants has shifted relative to Hong and Yogo (2012). Hence a direct comparison is not appropriate. In addition, the median annualized basis is much stronger than in the benchmark period and indicating a mild contango of the futures curve of 5.68%.

This suggests that average storage costs exceed the associated convenience yield of the commodity portfolio (theory of storage) (Gorton et al. 2007). Moreover, the average contango could reflect the increased inflow of invested money into liquid (front-month) futures contracts.

4. Quantitative Analysis

Following the discussion of the underlying data, this section outlines the applied econometric framework and presents the obtained results.

4.1. Econometric Methodology

This study is using a multiple linear regression framework to assess whether changes in category-specific open interest contain predictive information for commodity excess returns during and after the financialization of commodity futures markets beyond traditional predictors. Employing a OLS multiple regression is common practice in academia when studying drivers of commodity excess returns and is utilized for instance by Hong and Yogo (2012), He et al. (2017), Haddad and Muir (2021) and Cotter (2023). The popularity of multiple regression in academia stems from the comparatively straight-forward interpretation of results and verifiability of the various model assumptions (see Chapter 4.2.5.).

In line with Hong and Yogo (2012), this analysis is based on nine regressions with a different composition of predictor variables. This allows to discuss the connectivity between the different predictors and to indicate which predictors share informational content.

While alternative statistical methods such as Granger causality tests (e.g. Büyüksahin and Harris 2011; Sanders et al. 2004) or GARCH-models (Generalized Autoregressive Conditional Heteroskedasticity) (e.g. Silvennoinen and Thorp 2013) have been applied in similar contexts, these models were considered less appropriate for this analysis.

The usability of Granger causality tests is limited when assessing the influence of multiple predictors and GARCH-models are specifically tailored to autocorrelated time series data.

4.2. Results of Regression Analysis

Table II: Results of the Regression Analysis

	Regression Analysis								
Predictor Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Short Rate	-0.71	-0.65	-0.71	-0.65	-0.63	-0.47	-0.73	-0.65	-0.45
	(-1.11)	(-1.02)	(-1.13)	(-1.01)	(-0.96)	(-0.68)	(-0.73)	(-0.64)	(-0.44)
Yield Spread	-0.96	-0.90	-0.96	-0.90	-1.07	-1.03	-0.98	-0.90	-1.01
	(-1.31)	(-1.25)	(-1.31)	(-1.24)	(-1.50)	(-1.43)	(-0.91)	(-0.84)	(-0.95)
Basis	0.76**	0.69**	0.76**	0.67*	0.56	0.45	0.76**	0.68*	0.48
	(2.46)	(2.17)	(2.42)	(2.15)	(1.63)	(1.20)	(2.28)	(1.93)	(1.25)
Category 1 Open Interest		*1.49***		*1.54***		*1.02*		*1.49***	*0.87*
		(2.01)		*(2.03)*		*(1.35)*		*(1.96)*	*(1.30)*
Category 2 Open Interest		*-0.54*		*-0.43*		*-0.57*		*-0.54*	
		(-0.69)		*(-0.51)*		*(-0.73)*		*(-0.57)*	
Category 3 Open Interest		*-1.18***		*-1.15**		*-1.11**		*-1.17***	*-1.10***
		(-2.04)		*(-1.95)*		*(-1.93)*		*(-2.11)*	*(-1.97)*
Category 4 Open Interest		*0.27*		*0.28*		*0.32*		*0.27*	*0.24*
		(0.51)		*(0.55)*		*(0.61)*		*(0.49)*	*(0.50)*
Commodity Returns 12-month geo. avg.			0.01	-0.22					-0.37
			(0.05)	(-0.41)					(-0.73)
Market Imbalance					*0.53**	0.66*			0.67*
					(1.95)	(1.74)			(1.71)
Chicago Fed National Activity Index							-0.09	-0.01	-0.02
							(-0.06)	(-0.01)	(-0.01)
R2 (in %)	4.1	6.7	4.1	6.8	5.5	7.9	4.2	6.7	7.9

Note: Level of significance of standardized coefficients are indicated using stars: * == P ≤ 0.10; ** == P ≤ 0.05; *** == P ≤ 0.01

Summary of the regression analysis focusing on the predictability of commodity excess returns by open interest. All predictor variables are lagged one month. Standardized coefficients with heteroskedasticity-consistent t-statistics in parentheses are reported. Significance-level is represented by the stars (see note). The sample period is 2006:06 - 2024:12.

Table II. presents the results of the performed regression analyses. To facilitate interpretation of the results of the analysis, all (lagged) predictor variables are standardized. Coefficients can be interpreted as percentage point changes in the monthly excess returns per one-standard-deviation change in the predictor variables (Hong and Yogo 2012).

4.2.1. Results of Baseline Regression

The first column of Table II. contains a baseline regression consisting of the short rate, the yield spread and the basis, which were identified as influential and significant predictors in the study by Hong and Yogo (2012). The analysis of the baseline regression shows significant differences to the benchmark analysis from 1966 to 2008 (see Table A.II.).

Although the coefficient of the short rate (-0,71) and yield spread (-0.96) predictors are economically relevant and remain negatively associated with the portfolio's excess returns, the two predictors are not significant anymore (at a 10%-significance-level). This indicates a diminished role of conventional (macro and financial) indicators in the post-financialization era – potentially due to the long-lasting phase of low interest rates and the associated quantitative easing following the Global Financial Crisis (GFC) (see Figure A.VI.). Regarding the short rate, the negative relationship can be explained by an accompanying higher discount rate, which automatically reduces excess returns (Cotter 2023). In addition, rising interest rates are an indicator of tighter monetary conditions, which could reduce future demand. Similarly, an increase in the yield spread implies higher borrowing costs for corporates, which traditionally coincides with a worsening economic environment and recession expectations – leading to lower excess returns. A more striking aspect is that although the basis is still a significant predictor, it now bears a positive relation to the excess returns of the portfolio. Ceteris paribus, a standard deviation increase in the basis, leads to an expected increase of the excess returns by 0.75%. Previously, Hong and Yogo (2012) had found a negative relationship. Although the coefficient of the basis initially appears contradictory, it is in line with results of Silvennoinen and Thorp (2013) for the positive relation between lagged basis and aggregated monthly returns. Part of the explanation could be that historically over the last decades strong positive basis has coincided with a subsequent strong recovery, such as the Covid-19 crash or the GFC, which also led to a sharp rise in the basis in 2008/09 (see Figure A.V.). While the explanatory power of the baseline regression is very limited with an R2 of 4.1%, this is in line with the explanatory power in Hong and Yogo (2012) and Cotter (2023).

By incorporating open interest by category of market participant as separate independent variables, the explanatory power of the regression model raises sharply to a R2 of 6.7% (see column 2 of Table II.). Just Category 1 (1.49) and Category 3 (-1.18) coefficients show significance at the 5%-significance-level, whereas coefficients of open interest growth rates for Category 2 (-0.54) and Category 4 (0.27) display no significance.

The significant positive coefficient for the open interest growth rate of Category 1 implies that a one-standard deviation increase in open interest, ceteris paribus increases expected excess returns by 1.49%. In contrast, a one-standard-deviation increase in the open interest of Category 3 leads ceteris paribus to a 1.18% decrease in the expected excess returns. Whilst these results are not strictly consistent with the theory of backwardation, they confirm the results of Kang et al. (2020). In their work, they have shown that short-term (weekly observations) physical commodity market participants (Category 1) act as providers of liquidity and money managers (Category 3) as consumers of liquidity. Kang et al. (2020) identified non-commercial market participants as predominantly momentum traders, whereas commercial traders appear as 'contrarians'. Risk-averse commercial market participants provide liquidity to meet the short-term trading demands of non-commercial traders, for which the commercials are rewarded with a liquidity provision premium (Kang et al. 2020). The coefficients of the regression analysis in the second column thus indicate that the findings of Kang et al. (2020) on the liquidity premium apply not only in the short term, but also on a monthly, medium-term level. The results are also in line with the "convective risk flow" hypothesis of Cheng et al. (2015) which states that especially in times of higher volatility speculative traders tend to reduce their positions while hedgers take the other side. Hence this could explain the associated positive coefficients for Category 1 in the form of a risk premium. The insignificance of the ambiguously defined Category 3 is in accordance with earlier research of Hamilton and Wu (2015) and Cheng et al. (2015). This also applies to Category 4, where other researchers such as Kang et al. (2020) have similarly found no significance for the prediction of excess returns.

4.2.2. Informational Content of Historic Returns

In the columns 3 and 4, the lagged historic 12-month geometric average of commodity futures returns is added as a control variable to the baseline regression. With a t-statistic of 0.05, this predictor has no noticeable influence on the baseline regression and the coefficient of 0.01 implies no economic relevance. Thus, historical average returns bear limited forecasting power. Consistent with the underlying results of Hong and Yogo (2012) this observation implies, that there is no evidence of long-term momentum in futures excess returns and open interest growth rates are no proxy for long-term momentum.

4.2.3. Informational Content of Market Imbalance

Column 5 of Table II. introduces the market imbalance. Typically, producers are net short to hedge their physical exposure. The imbalance thus describes the directional hedging pressure on commercial participants. The market imbalance coefficient is statistically significant on a 10-%-significance-level and with a positive coefficient of 0.53 economically relevant. This finding suggests that when commercial participants offload a higher share of price risk to other market participants (e.g. money managers), they demand a risk premium in return, resulting in a positive excess return for long futures positions (Kang et al. 2020). When comparing column 5 with column 6, it is clear that market imbalance was introduced at the expense of the predictive power of Category 1 open interest movements. The open interest growth rate for Category 3 remains a significant predictor and does not lose predictive power. In addition, it appears that the market imbalance is in competition with the predictive informational content of the basis, which goes beyond the informational content of the open interest growth rates for Category 1. While the market imbalance can be understood as a direct measure of the hedging pressures, the basis also reflects hedging pressure indirectly. This is confirmed by the work of Acharya et al. (2013) who demonstrated that futures risk premia and spot price movements have one important common driver – the hedging demand of producers. Thus, linking market imbalance and basis. The remaining predictive power of the basis is presumably due to additional factors not captured by market imbalance, such as storage costs or convenience yield.

4.2.4. Informational Content of US-Economic Activity

Columns 7 and 8 of Table II. examine the predictive power of the CFNAI predictor, which depicts macroeconomic activity in the USA. Yet the inclusion in the baseline prediction demonstrates that the lagged CFNAI possesses no significance (t-statistic of -0.06) for the expected commodity futures excess returns. This is somewhat surprising at first, as Hong and Yogo (2012) were able to identify a significance of the CFNAI predictor for the period 1966 – 2008. There could be several possible explanations for this difference. First, as explained in Chapter 2.1., commodity futures in the course of financialization are becoming less depending on supply and demand drivers, and thus less tied to real (US)-economic activity (Tang and Xiong 2012). In addition, the world economy has become increasingly globalized. A study conducted by Yin and Han (2016) covering the period from 1999 to 2012 found that China's macroeconomic indicators also have a significant influence on price fluctuations for selected commodities, thereby reducing the impact of US-focused macroeconomic indicators.

4.2.5. Comprehensive Regression and Discussion

To evaluate the overall explanatory power of the predictors and to validate compliance with the assumptions of an OLS regression, a comprehensive regression including all predictors is presented in column 9.

Notably, the predictor for Category 2 was excluded from this model due to the high correlation between Category 1 and Category 2 of approx. 0.93 and variance inflation factors (VIFs) exceeding 10 – indicating multicollinearity (see Table A.III.). This is economically plausible as Category 2, in addition to the aforementioned CITs, also includes intermediaries who help producers to hedge the price risk, resulting in structurally mirrored positions (CFTC 2025b).

Excluding Category 2, the VIFs for the remaining predictors fall below 10, and thus to a bearable level of multicollinearity.

The following diagnostics approve the validity of the model and the conformity with OLS-assumptions. The Augmented Dickey-Fuller-Test, which is used to check whether the dependent variable is stationary, shows significance at a 5-%-level – thus the dependent variable is stationary and allows for more causal conclusions (Irwin et al. 2009). At the same time, the regression residuals indicate acceptable slight signs of positive autocorrelation with a Durbin-Watson-Test score of approx. 1.75. As a score of 2.0 would equate to no autocorrelation, the slight positive autocorrelation is due to the utilization of 12-month geometric averages of the open interest growth rates. Additionally, heteroskedasticity-robust standard errors are used in the model. These are designed to reduce heteroskedasticity and can also counteract a possible bias in the coefficients due to the slight positive autocorrelation (Cotter 2023). Performing the Breusch-Pagan test, confirms there is no heteroskedasticity in the model. Finally, the normal distribution of the residuals was tested (see Figure A.VII.). Although there are left-skewed outliers, which represent black-swan events in financial markets (e.g. GFC or Covid-19), the distribution of the residuals is largely in line with the normal distribution. Consequently, the assumptions of an OLS regression for the comprehensive regression model are fulfilled. This ensures that the results of the OLS regression are statistically robust and unbiased, and that the OLS estimator is considered to be BLUE (Best Linear Unbiased Estimator). When comparing column 9 with the respective columns 1 – 8, the coefficients and t-statistics remain stable, implying that the prior observations can be considered unbiased and robust. Therefore, the additional verification of the assumptions for each regression was considered unnecessary.

Most critically, column 9 shows that open interest growth rates remain important predictors of commodity futures excess returns when controlling for traditional predictors. Particularly noteworthy is the persistent significance of Category 3.

A one-standard-deviation increase in respective open interest growth rates is associated, ceteris paribus, with a 1.10% decrease in expected excess returns. Challenging the prevailing public narrative that increased speculative participation in commodity futures markets does generally lead to inflated prices (Irwin et al. 2009). While the Category 1 coefficient shows economic relevance (coefficient of 0.87), it remains slightly insignificant when controlling for market imbalance. Still, the positioning of Category 1 remains relevant, as the market imbalance predictor remains statistically (on a 10%-significance-level) and economically (coefficient of 0.67) significant when controlling for all other predictors. Thus, increasing participation by producers, especially when driven by an imbalanced short exposure, is associated with an increase in expected excess returns.

Overall, the analysis reaffirms emerging literature focusing on intermediary-driven asset pricing going beyond traditional theories within commodity markets. Predictors that represent the integrated market view (Hong and Yogo 2012), i.e. that commodity prices move according to the broad financial market, such as short rate, yield spread or CFNAI, show little or no significance. Predictors representing the segmented market view (Hong and Yogo 2012), i.e. commodity prices move in accordance with idiosyncratic supply- and demand factors, such as market imbalance and commodity basis, remain (partly) significant. Market imbalance and basis, which are (indirectly) dependent on the positioning of the intermediaries, therefore pick up on the same informational content as (categorized) open interest.

5. Conclusion

This study examined whether market participant-specific changes in open interest can explain excess returns in commodity futures markets during the intra- and post-financialization period (2006 – 2024) beyond traditional predictors. Hong and Yogo already indicated in their 2012 paper that conventional theories such as the theory of backwardation or hedging pressure are no longer sufficient to explain movements in commodity futures markets. Compared to the observation period in the benchmark paper from 1966 to 2008, the commodity futures markets have evolved. As shown in Chapter 3.5., a substantial part of the capital inflows associated with the financialization of the commodity futures markets occurred prior to the analysis sample period. With a 12-month geometric average growth rate in total open interest of 0.75%, this is notably below the growth rate of 1.47% reported by Hong and Yogo (2012). Yet, the remaining growth is significantly driven by Category 3 and 4, representing trading motives not directly related to hedging physical exposure.

The results of this study support, that changes in category-specific open interest, particularly from producers (Category 1) and money managers (Category 3), explain variations in monthly excess returns that are not captured by conventional financial and macroeconomic predictors. This is consistent with modern intermediary asset pricing theories focusing on new perspectives on risk sharing between market participants (Kang et al. 2020; Cheng et al. 2015). More precisely, contrary to public perception and in line with other studies, this study finds that speculative inflow does not inevitably lead to inflated commodity prices and higher excess returns. Instead, a one-standard-deviation increase in money managers open interest is associated with a 1.10% decrease in excess returns. By contrast, producers appear to demand additional compensation for absorbing additional risk and thus a one-standard-deviation increase in their open interest growth rate is associated with a 0.87% increase in excess returns. While this coefficient becomes insignificant when controlling for market imbalance, the proportional short positioning of producers expressed in terms of market imbalance remains significant (at a 10%-significance-level). An increase in market imbalance, implying a larger share of short positions, by one standard deviation is associated with 0.68% higher excess returns, ceteris paribus. The positioning of swap dealers, which have played an important role in the financialization of commodity markets, is insignificant when explaining excess returns.

Nevertheless, these conclusions come with important restrictions. The analysis is following the approach of Hong and Yogo (2012) and is based on an aggregated level of open interest growth rates and is not disentangling long and short exposures. This prevents a conclusive evaluation of the performance of individual market participants and their differentiated role in risk absorption and liquidity provision. Furthermore, it must be noted that the separation of categories by the CFTC is imprecise. For instance, swap dealers can act as hedgers on behalf of producers but are still assigned to Category 2. Or hybrid institutions that pursue both hedging and speculative motives and are therefore difficult to categorize. As a result, it is difficult to assess causal risk-sharing dynamics and thus to assess the influence of specific market participants. In addition, the available data does not indicate trade direction (who initiated or accommodated the trades). Consequently, the interpretation of the results is mainly based on findings of previous studies as this analysis is not intended to develop a separate theory, but to back existing theories with empirical results. Causal interpretations are thus vulnerable to simultaneity and endogeneity as open interest could reflect rather than anticipate price changes (Cheng et al. 2015). While the study contributes to the structural understanding of excess returns in a noisy market, the statistical evidence should not be equated with economic significance. Previous studies have demonstrated that CFTC data is already priced in as part of the efficient market and therefore restricts its commercial applicability (Dreesman et al. 2023).

Although Hong and Yogo (2012) recommended including the positioning of traders in inflation forecasting models, this integration is still – to our knowledge – widely missing. The results highlight that the market participants' positioning contain forward-looking information that is not captured by macro aggregates. As the commodity futures markets continue to evolve into financialized, intermediated markets, the development of asset pricing models that focus on risk sharing, liquidity provision, and institutional constraints is essential for both theory and policy. This study aims to provides empirical support for this objective.

References

Acharya, Viral, Lars Lochstoer, and Tarun Ramadorai. 2013. “Limits to Arbitrage and Hedging: Evidence from Commodity Markets.” Journal of Financial Economics, 109(2): 441–465. https://doi.org/10.1016/j.jfineco.2013.03.003

Alquist, Ron, Lutz Kilian, and Robert Vigfusson. 2013. “Forecasting the Price of Oil.” Handbook of Economic Forecasting, 2: 427–507. https://doi.org/10.1016/B978-0-444-53683-9.00008-6

Barsky, Robert, and Lutz Kilian. 2002. “Oil and the Macroeconomy Since the 1970s.” Journal of Economic Perspectives, 18(4): 115–134. https://doi.org/10.1257/0895330042632708

Basak, Suleyman, and Anna Pavlova. 2016. “A Model of Financialization of Commodities.” Journal of Finance, 71(4): 1511–1556. https://doi.org/10.1111/jofi.12408

Bonnier, Jean-Baptiste. 2021. “Speculation and Informational Efficiency in Commodity Futures Markets.” Journal of International Money and Finance, 117: 102457. http://dx.doi.org/10.1016/j.jimonfin.2021.102457

Brunetti, Celso, Bahattin Büyükşahin, and Jeffrey Harris. 2016. “Speculators, Prices, and Market Volatility.” Journal of Financial and Quantitative Analysis, 51(5): 1545–1574. https://doi.org/10.1016/j.jimonfin.2021.102457

Büyüksahin, Bahattin, and Jeffrey Harris. 2011. “Do Speculators Drive Crude Oil Futures Prices?.” The Energy Journal, 32(2): 167–202. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol32-No2-7

Büyüksahin, Bahattin, and Michel Robe. 2014. “Speculators, Commodities and Cross-Market Linkages.” Journal of International Money and Finance, 42: 38–70. https://doi.org/10.1016/j.jimonfin.2013.08.004

CFTC. 2025a. "Commitments of Traders." Commodity Futures Trading Commission. Accessed February 25, 2025. https://www.cftc.gov/MarketReports/CommitmentsofTraders/index.htm.

CFTC. 2025b. "Disaggregated Commitments of Traders Report: Explanatory Notes." Commodity Futures Trading Commission. Accessed February 21, 2025. https://www.cftc.gov/sites/default/files/idc/groups/public/@commitmentsoftraders/documents/file/disaggregatedcotexplanatorynot.pdf.

CFTC. 2025c. "Economic Purpose of Futures Markets and How They Work." Commodity Futures Trading Commission. Accessed February 15, 2025. https://www.cftc.gov/LearnAndProtect/ AdvisoriesAndArticles/economicpurpose.html.

CFTC. 2025d. "Explanatory Notes." Commodity Futures Trading Commission. Accessed February 21, 2025. https://www.cftc.gov/MarketReports/CommitmentsofTraders/ExplanatoryNotes/index.htm.

Cheng, Ing-Haw, Andrei Kirilenko, and Wei Xiong. 2015. "Convective Risk Flows in Commodity Futures Markets." Review of Finance, 19(5): 1733–1781. https://doi.org/10.1093/rof/rfu043

Cheng, Ing-Haw, and Wei Xiong. 2014. "Financialization of Commodity Markets." Annual Review of Financial Economics, 6(1): 419–441. https://doi.org/10.1146/annurevfinancial-110613-034432

Cotter, John. 2023. "Commodity Futures Return Predictability and Intertemporal Asset Pricing." Journal of Commodity Markets, 31: 100289. https://doi.org/10.1016/j.jcomm.2022.100289

Dreesman, Simon, Tim Herberger, and Michel Charifzadeh. 2023. "The Commitment of Traders Report as a Trading the Commitment of Trader Report as a Trading Signal?

Short-Term Price Reversals and Market Efficiency in the US-Futures Market." International Journal of Financial Markets and Derivatives, 9(1): 76–113. https://doi.org/10.1504/IJFMD.2023.129093

Floros, Christos, and Enrique Salvador. 2016. "Volatility, Trading Volume and Open Interest in Futures Markets." International Journal of Managerial Finance, 12(5): 629–653. http://dx.doi.org/10.1108/IJMF-04-2015-0071

Gargano, Antonio, and Allan Timmermann. 2014. "Forecasting Commodity Price Indexes Using Macroeconomic and Financial Predictors." International Journal of Forecasting, 30(3): 825–843. http://dx.doi.org/10.1016/j.ijforecast.2013.09.003

Gilbert, Christopher. 2010. "How to Understand High Food Prices." Journal of Agricultural Economics, 62(2): 398–425. http://dx.doi.org/10.1111/j.1477-9552.2010.00248.x

Gorton, Gary, Fumio Hayashi, and K. Geert Rouwenhorst. 2007. "The Fundamentals of Commodity Futures Returns." Review of Finance, 17(1): 35–105. http://dx.doi.org/10.1093/rof/rfs019

Haddad, Valentin, and Tyler Muir. 2021. "Do Intermediaries Matter for Aggregate Asset Prices?" Journal of Finance, 76(6): 2719–2761. http://dx.doi.org/10.1111/jofi.13086

Hamilton, James D., and Jing Wu. 2015. "Effects of Index-fund Investing on Commodity Futures Prices." International Economic Review, 56(1): 187–205. http://dx.doi.org/10.1111/iere.12099

He, Zhiguo, Brian Kelly, and Asaf Manela. 2017. "Intermediary Asset Pricing: New Evidence from Many Asset Classes." Journal of Financial Economics, 126(1): 1–35. http://dx.doi.org/10.1016/j.jfineco.2017.08.002

Hong, Harrison, and Motohiro Yogo. 2011. “Appendix to "What Does Futures Market Interest Tell Us About the Macroeconomy and Asset Prices?”.” Unpublished Working Paper. Federal Reserve Bank of Minneapolis.

Hong, Harrison, and Motohiro Yogo. 2012. “What Does Futures Market Interest Tell Us About the Macroeconomy and Asset Prices?” Journal of Financial Economics, 105(3): 473–490. http://dx.doi.org/10.1016/j.jfineco.2012.04.005

Irwin, Scott, Dwight Sanders, and Robert Merrin. 2009. “Devil or Angel? The Role of Speculation in the Recent Commodity Price Boom (And Bust).” Journal of Agricultural and Applied Economics, 41(2): 377–391. http://dx.doi.org/10.1017/S1074070800002856

Kaldor, Nicholas. 1939. “Speculation and Economic Stability.” The Review of Economic Studies, 7(1): 1–27. http://dx.doi.org/10.2307/2967593

Kang, Wenjin, Geert Rouwenhorst, and Ke Tang. 2020. “A Tale of Two Premiums: The Role of Hedgers and Speculators in Commodity Futures Markets.” Journal of Finance, 75(1): 377–417. http://dx.doi.org/10.1111/jofi.12845

Keynes, John Maynard. 1930. “A Treatise on Money.” The Applied Theory of Money, 2. http://dx.doi.org/10.1007/978-1-349-00804-9

Norland, Erik. 2025. “Are Extremely Tight U.S. Credit Spreads Underpricing Risk?.” CME Group. Accessed April 08, 2025. https://www.cmegroup.com/insights/economic-research/2025/are-extremely-tight-us-credit-spreads-underpricing-risk.html.

Ripple, Ronald, and Imad Moosa. 2009. “The Effect of Maturity, Trading Volume, and Open Interest on Crude Oil Futures Price Range-Based Volatility.” Global Finance Journal, 20(3): 209–219. http://dx.doi.org/10.1016/j.gfj.2009.06.001

Sanders, Dwight, Keith Boris, and Mark Manfredo. 2004. "Hedgers, Funds, and Small Speculators in the Energy Futures Markets: An Analysis of the CFTC's Commitments of Traders Reports." Energy Economics, 26(3): 425–445. http://dx.doi.org/10.1016/S0140-9883(04)00020-9

Silvennoinen, Annastiina, and Susan Thorp. 2013. "Financialization, Crisis and Commodity Correlation Dynamics." Journal of International Financial Markets, Institutions and Money, 24: 42–65. http://dx.doi.org/10.1016/j.intfin.2012.11.007

Szymanowska, Marta, Frans de Roon, Theo Nijman, and Rob van den Goorberg. 2014. "An Anatomy of Commodity Futures Risk Premia." Journal of Finance, 69(1): 453–482. http://dx.doi.org/10.1111/jofi.12096

Tang, Ke, and Wei Xiong. 2012. "Index Investment and the Financialization of Commodities." Financial Analysts Journal, 68(6): 54–74. http://dx.doi.org/10.2469/faj.v68.n6.5

Yin, Libo, and Liyan Han. 2016. "Macroeconomic Impacts on Commodity Prices: China Vs. The United States." Quantitative Finance, 16(3): 489–500. http://dx.doi.org/10.1080/14697688.2015.1018308

Yin, Libo, Jing Nie, and Liyan Han. 2020. "Intermediary Asset Pricing in Commodity Futures Returns." Journal of Future Markets, 40(11): 1711–1730. http://dx.doi.org/10.1002/fut.22099

Appendix

Table A.I.: Overview of Commodities included in Portfolio by Sector

Sector	Commodity	Exchange	Start Date of Portfolio Inclusion	Observations	Spot Price available?
Agriculture	Butter	CME	September 2006	181	Yes
	Cocoa	ICE	July 2006	223	Yes
	Coffee	ICE	July 2006	223	Yes
	Corn	CBOT	July 2006	223	Yes
	Cotton	ICE	July 2006	223	Yes
	Lumber	CME	August 2022	30	No
	Oats	CBOT	July 2006	196	No
	Orange juice	ICE	July 2006	223	No
	Rough rice	CBOT	July 2006	223	No
	Soybean meal	CBOT	July 2006	223	Yes
	Soybean oil	CBOT	July 2006	223	Yes
	Soybeans	CBOT	July 2006	223	Yes
	Sugar	ICE	July 2006	223	Yes
	Wheat	CBOT	July 2006	223	Yes
Energy	Crude oil	NYMEX	July 2006	223	Yes
	Gasoline	NYMEX	July 2006	223	Yes
	Heating oil	NYMEX	July 2006	223	Yes
	Natural gas	NYMEX	July 2006	223	Yes
	Propane	NYMEX	Mai 2010	177	No
Livestock	Feeder cattle	CME	July 2006	223	Yes
	Lean hogs	CME	July 2006	223	No
	Live cattle	CME	July 2006	223	No
Metals	Aluminium	COMEX	November 2015	97	No
	Copper	COMEX	July 2006	223	Yes
	Gold	COMEX	July 2006	223	Yes
	Palladium	NYMEX	August 2006	222	Yes
	Platinum	NYMEX	July 2006	223	Yes
	Silver	COMEX	July 2006	223	No

Table A.II.: Regression Results of Benchmark Analysis by Hong and Yogo (2012)

Predictor Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short rate	-0.51	-0.48	-0.44	-0.50	-0.55	-0.50	-0.52	-0.55
	(-2.42)	(-1.85)	(-2.10)	(-1.98)	(-2.39)	(-1.99)	(-2.50)	(-2.12)
Yield spread	-0.51	-0.44	-0.37	-0.48	-0.45	-0.42	-0.58	-0.57
	(-2.68)	(-2.03)	(-2.03)	(-2.41)	(-2.17)	(-1.90)	(-2.78)	(-2.54)
Commodity basis	-0.57	-0.52	-0.56	-0.52	-0.59	-0.53	-0.66	-0.62
	(-2.05)	(-1.91)	(-2.01)	(-1.91)	(-2.04)	(-1.92)	(-2.02)	(-1.88)
Commodity market interest		0.73		0.77		0.69		0.68
		(2.50)		(1.85)		(2.42)		(1.88)
Commodity returns 12-month geo. avg.			0.32	-0.08				
			(1.39)	(-0.22)				
Commodity market imbalance					0.34	0.12		
					(1.50)	(0.60)		
Chicago Fed National Activity Index							0.47	0.30
							(2.09)	(0.93)
R^2 (in %)	2.58	4.96	2.98	4.98	3.01	5.02	4.26	6.2

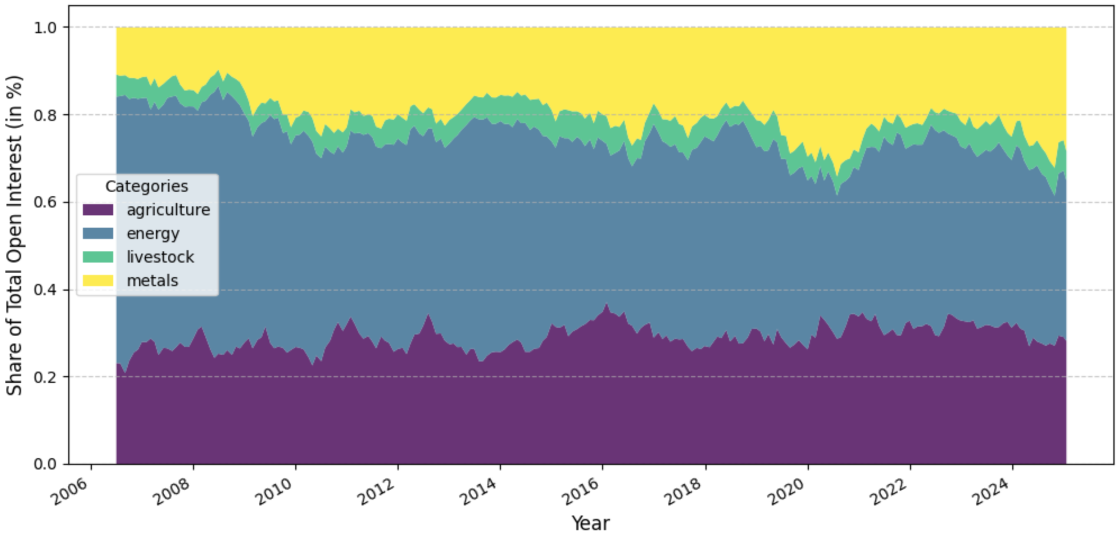
Summary of the regression analysis of Hong and Yogo (2012) focusing on the predictability of commodity excess returns by open interest. All predictor variables are lagged one month. Standardized coefficients with heteroskedasticity-consistent t-statistics in parentheses are reported. The sample period is 1966:01 - 2008:12.

Table A.III.: Variance Inflation Factors of Regression Analysis

	Variance Inflation Factors (VIF)	
(Lagged) Predictor	**Before exclusion of Category 2**	**After exclusion of Category 2**
Category 1 OI-growth rate (12m)	11.52	9.01
Category 2 OI-growth rate (12m)	11.29	/
Category 3 OI-growth rate (12m)	6.12	6.01
Category 4 OI-growth rate (12m)	6.72	6.10
Commodity returns 12-month geo. avg.	5.00	4.43
Short rate	4.55	4.48
Yield spread	4.76	4.70
Commodity basis	1.41	1.41
Market imbalance	2.66	2.66
CFNAI	1.11	1.11

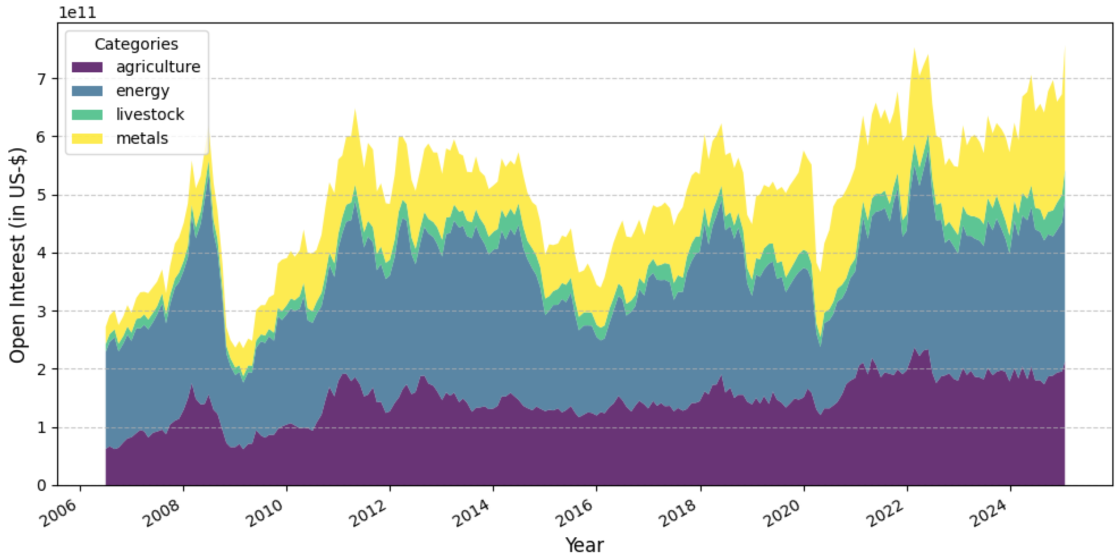
Overview of the VIF's of the regression in column 9 of Table 2. Before and after the exclusion of Category 2 open interest growth rates highlighting the present multicollinearity without exclusion.

Figure A.I.: Share of Dollar Open Interest by Sector



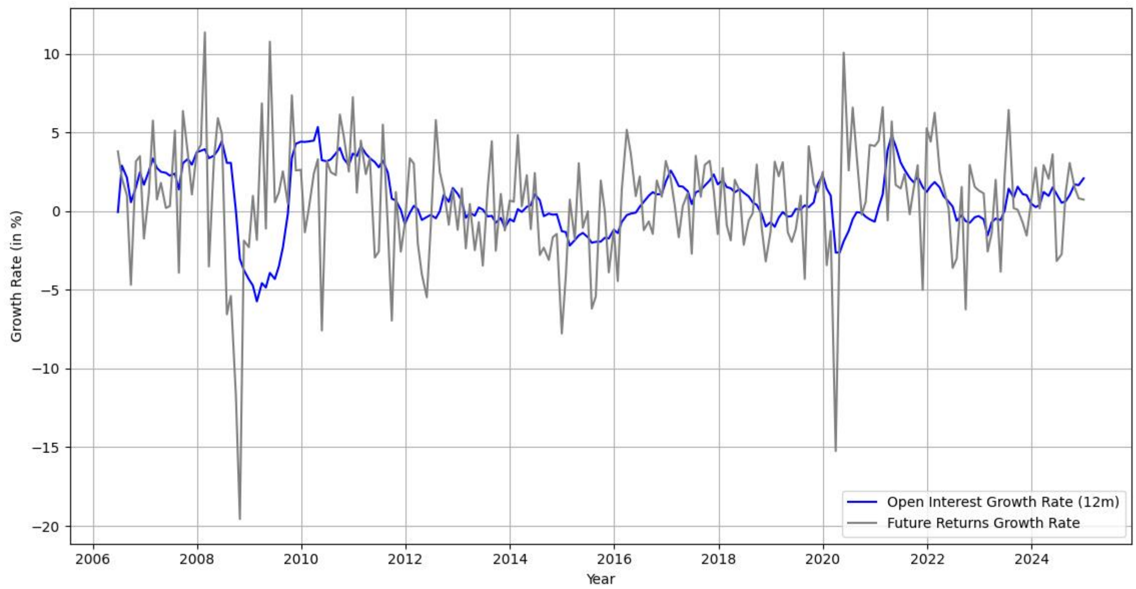
Share of US-dollar open interest by sector of selected commodities.
The sample period is 2006:06 – 2024:12.

Figure A.II.: Dollar Open Interest by Sector



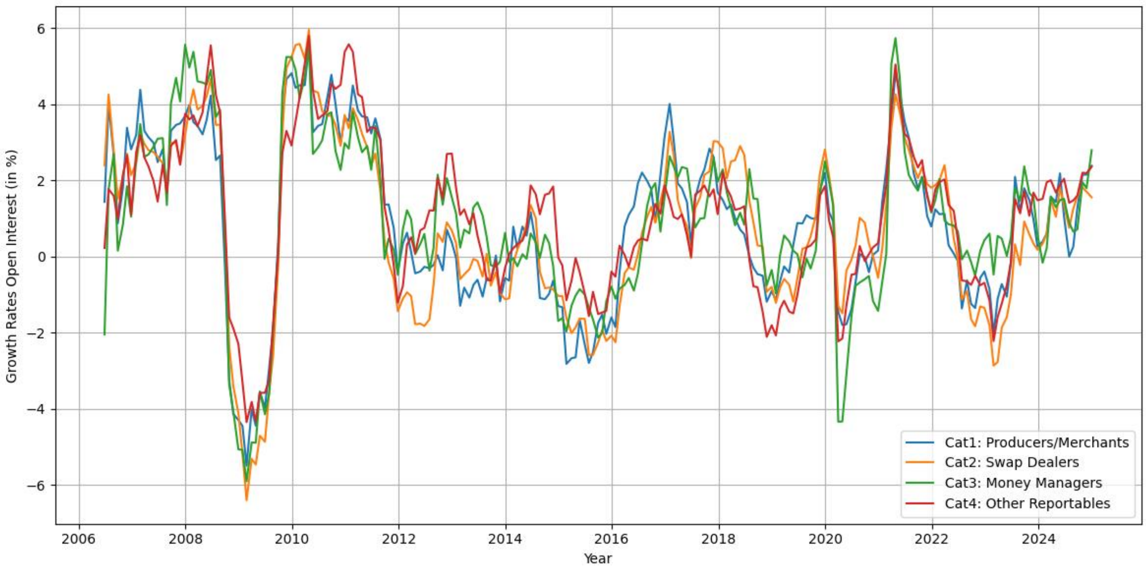
Development of US-dollar open interest by sector of selected commodities over time. The sample period is 2006:06 – 2024:12.

Figure A.III.: Portfolio Return and Open Interest Growth Rates (12m)



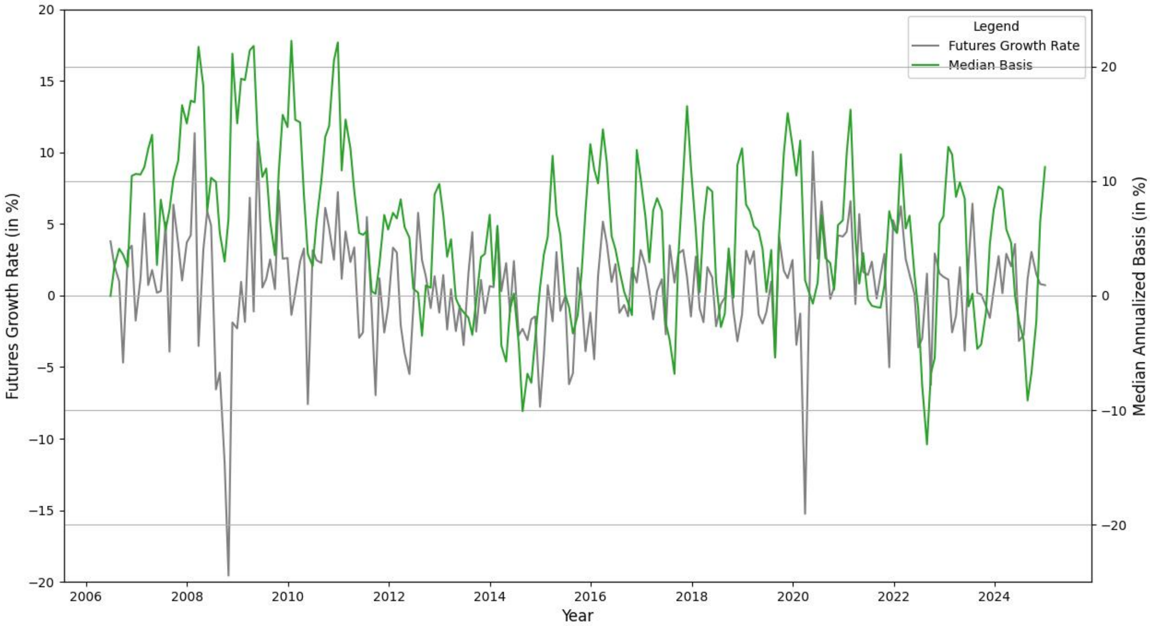
Open interest growth rates (12-month geometric average) and returns growth rate of the portfolio. The sample period is 2006:06 – 2024:12.

Figure A.IV.: Open Interest Growth Rates by Category of Market Participants



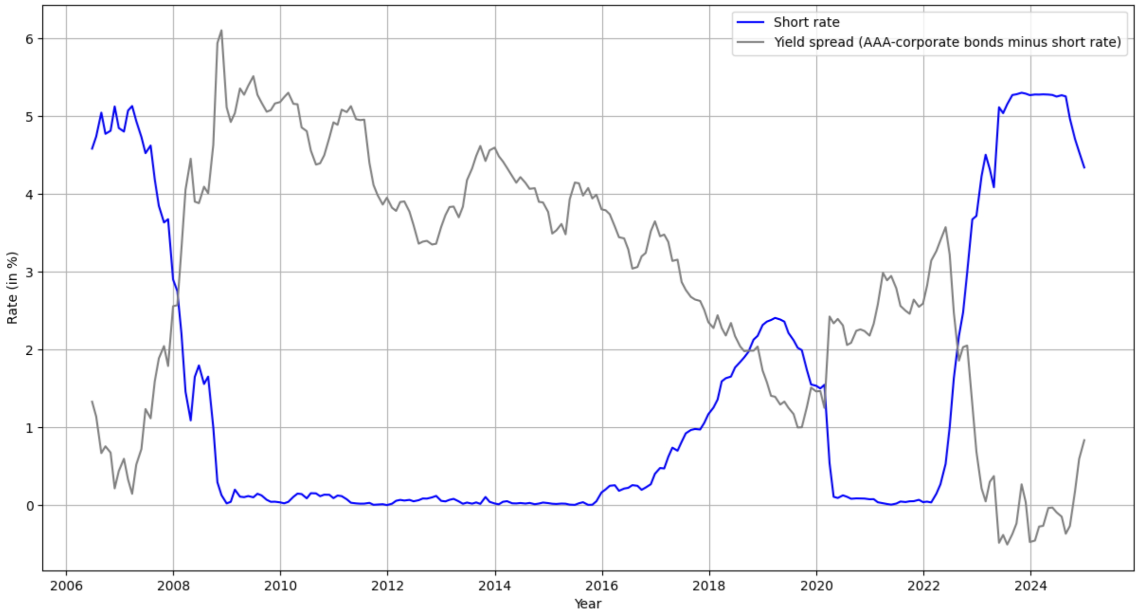
Open interest growth rates (12-month geometric average) by category of market participants. The sample period is 2006:06 – 2024:12.

Figure A.V.: Open Interest Growth Rates and Basis of Portfolio



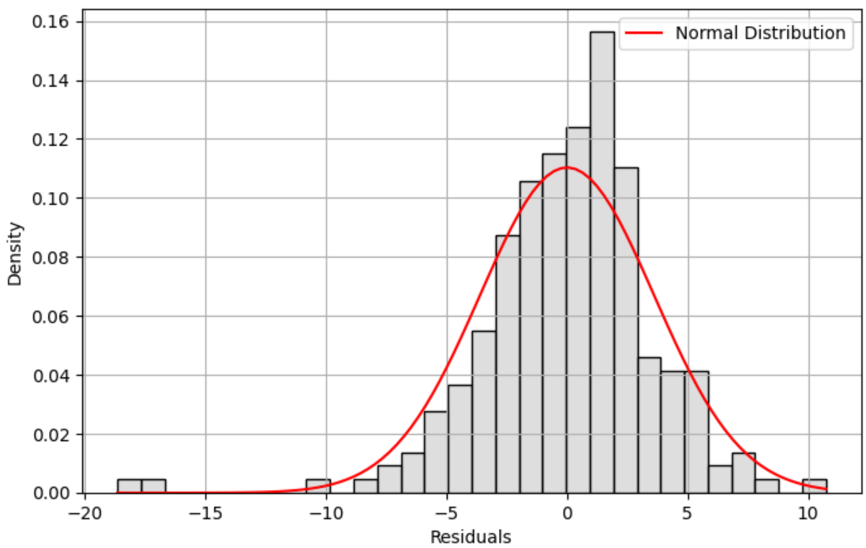
Annualized basis and excess return growth rate of the portfolio.
The sample period is 2006:06 – 2024:12.

Figure A.VI.: Short Rate and Yield Spread over Time



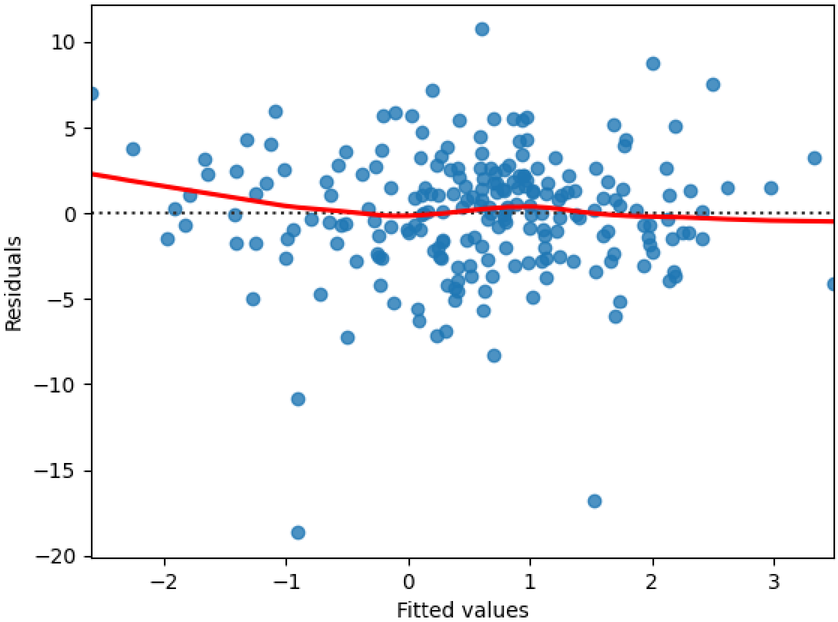
Short rate and yield spread over time in percent as provided by FRED.
The sample period is 2006:06 – 2024:12.

Figure A.VII.: Distribution of Residuals of Regression Model



Distribution of residuals of regression model 9 (see Table II.) vs. normal distribution.
The sample period is 2006:06 – 2024:12.

Figure A.VIII.: Residuals of Regression Model vs. Fitted Values



Residuals of regression model 9 (see Table II.) vs. the fitted values to confirm linearity of regression model. The sample period is 2006:06 – 2024:12.